

A New BFA-Based Approach for Optimal Sitting and Sizing of Distributed Generation in Distribution System

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Abstract

This paper proposes an approach based on Bacterial Foraging Algorithm (BFA) for optimal placement of Distribution Generations (DGs). The optimal sitting and sizing of distributed generation is formulated as a multi-objective function including the network power losses minimization and voltage profile improvement. BFA algorithm has been employed to optimize the problem. To demonstrate the effectiveness of the proposed approach, it has been applied to 33 and 69 bus systems. The results of the proposed approach are compared with those of Genetic Algorithm (GA) and also Shuffled Frog Leaping Algorithm (SFLA) to reveal its strong performance.

Keywords

Distributed Generation; Optimal Placement; Bacterial Foraging Algorithm (BFA); Genetic Algorithm (GA); Shuffled Frog Leaping Algorithm (SFLA)

Introduction

Distributed generation is expected to play an increasing role in emerging electrical power systems. Studies have predicted that DG will be a meaningful percentage of all new generations going on lines. It is predicted that they are about 20% of the new generations being installed [1]. Optimization techniques should be employed for deregulation of the power industry, by applying the best allocation of the distributed generations (DGs). The advancement in technology and the demand of the customers for cheap and reliable electric power has led to an increasing interest in distributed generation. The issues related to reliability and maintenance has impeded the penetration of DG resources in distribution systems [2-6]. The DG units might bring different benefits such as: network investment deferral [7], active loss reduction [8-10], voltage profile improvement [22], and reliability improvement [12-14]. The benefits of DG units highly

depend on the size and location of them in the network. Many methods have been proposed in the literature to find the optimal location and size of DG units in the network which have considered various technical aspects such as: voltage limits, feeder capacity limits and number of installed DG units [15]. In [16], a GA method is proposed to minimize the distribution systems active power flow. In [17], a combination of GA and simulated annealing meta-heuristic methods is used to solve optimal DG power output. A TS method to size the DG optimally, as well as the reactive sources within the distribution system, is presented in [18]. A multi objective function is proposed to determine the optimal locations to place DGs in distribution system to minimize power loss of the system and enhance reliability improvement and voltage profile [19]. [20] Considered an analytical expression to calculate the optimal size and an effective methodology to identify the corresponding optimum location for DG placement for minimizing the total power losses in primary distribution systems. The selection of the best places for installation and the preferable size of the DG units in large distribution systems is a complex combinatorial optimization problem. In [21], Lagrangian based approaches are used to determine optimal locations for placing DG, considering economic limits and stability limits. In [22-24], the authors succeeded in merging both the DG location and size in one optimization problem. The main factors included in the optimization problem were investment cost, operation cost, network configuration, active and reactive power costs, heat and power requirements, and voltage profile and system losses. Several methods have been adopted to solve such an optimization problem. Some of them rely on conventional optimization methods and others use artificial intelligent-based optimization methods. In some researches, the optimum location and size of a single

DG unit is determined [22], whereas in others the optimum locations and sizes of multiple DG units are determined [23]. In [25], a mixed integer linear program was formulated to solve the optimization problem. The objective was to optimally determine the DG plant mix on a network section. However, that required dealing with the power system approximately as a linear system which is not the real case. In [26], a tabu search (TS)-based method was proposed to find the optimal solution of their problem, but the TS is known to be time-consuming algorithm in addition to its ability to be trapped in a local minimum. In [22], a particle swarm optimization (PSO) algorithm was introduced to determine the optimum size and location of a single DG unit to minimize the real power losses of the system. The problem was formulated as one of the constrained mixed integer non-linear programming with the location being discrete and the size being continuous. However, the real power loss of the system was the only aspect considered in this work while trying to optimally find the size of only one DG unit to be placed. In [23], different scenarios were suggested for optimum distribution planning. One of these scenarios was to place multiple DG units at certain locations pre-determined by the electric utility distribution companies (DISCOs) aiming to improve their profiles and minimize the investment risk. In this paper, the problem of optimal DG location and sizing in distribution systems is formulated as a multi-objective optimization problem and BFA is used to solve this problem. The optimal DG location and sizing problem is converted to an optimization problem with the multi-objective function including the network power losses and better voltage regulation. The effectiveness of the proposed BFA is tested on 33 and 69 bus systems in comparison with the GA and SFLA through some performance indices. Results show that the proposed method provides the correct answers with high accuracy in the initial iterations in comparison with other methods and is superior to them.

Allocation of DG

The distribution systems are usually regulated through tap changing at substation transformers and by the use of voltage regulators and capacitors on the feeders. This form of voltage regulation assumes power flows circulating from the substation to the loads. DG introduces meshed power flows that may interfere with the traditional used regulation practices. Since the control of voltage regulation is usually based on radial

power flows, the inappropriate DG allocation can cause low or over-voltages in the network. On the other hand, the installation of DG can have positive impacts on the distribution system by enabling reactive compensation for a voltage control, reducing the losses, contributing for frequency regulation and acting as spinning reserve in main system fault cases.

Heuristic Optimization Methods

Genetic Algorithm (GA)

It is well known that GAs work are according to the mechanism of natural selection. Stronger individuals are likely to be the winners in a competitive environment. In practical applications, each individual is codified into a chromosome consisting of genes, that representing a characteristic of one individual. For identification parameters of a model, parameters are regarded as the genes of a chromosome, and a positive value, generally is known as the fitness value. It is used to reflect the degree of goodness of the chromosome. Typically, a chromosome is structured by a string of values in binary form, which the mutation operator can operate on any one of the bits, and the crossover operator can operate on any boundary of each two bits in the string [27]. Since, the parameters in our problem are real numbers, a real coded GA is used, in which the chromosome is defined as an array of real numbers with the mutation and crossover operators. Here, the mutation can change the value of a real number randomly, and the crossover can take place only at the boundary of two real numbers.

Shuffled Frog Leaping Algorithm (SFLA)

SFLA is a meta heuristic optimization method that mimics the memetic evolution of a group of frogs when seeking for the location having maximum amount of available food. The algorithm contains elements of local search and global information exchange [28]. The SFLA involves a population of possible solutions defined by a set of virtual frogs partitioned into subsets referred to as memeplexes. Within each memeplex, the individual frog holds ideas that can be influenced by the ideas of other frogs, and the ideas can evolve through a process of memetic evolution. Using a particle swarm optimization like method the SLFA simultaneously performs an independent local search in each memeplex. To ensure of global exploration, after a defined number of memeplex evolution steps (i.e. local search

iterations), the virtual frogs are shuffled and reorganized into new memplexes in a technique similar to that used in the shuffled complex evolution algorithm. In addition, to provide the opportunity for random generation of improved information, if the local search cannot find better solutions as random, virtual frogs are generated and substituted in the population. The local searches and the shuffling processes continue until defined convergence criteria are satisfied. The SFLA is described in details as follows. First, an initial population of N frogs $P = \{X_1, X_2, \dots, X_N\}$ is created as random. For S -dimensional problems (S variables), the position of a frog i^{th} in the search space is represented as $X_i = [x_1, x_2, \dots, x_{is}]^T$.

Afterwards, the frogs are sorted in a descending order according to their fitness. Then, the entire population is divided into m memplexes, that each containing n frogs (i.e. $N=m \times n$), in such a way that the first frog goes to the first memplex, the second frog goes to the second memplex, the m^{th} frog goes to the m^{th} memplex, and the $(m+1)^{th}$ frog goes back to the first memplex, etc.

Let M_k is the set of frogs in the k^{th} memplex, this dividing process can be described by the following expression:

$$M_k = \{X_{k+m(l-1)} \in P \mid 1 \leq k \leq n\}, (1 \leq k \leq m). \quad (1)$$

Within each memplex, the frogs with the best and the worst fitness are identified as X_b and X_w , respectively. Also, the frog with the global best fitness is identified as X_g . During memplex evolution, the worst frog X_w leaps toward the best frog X_b . According to the original frog leaping rule, the position of the worst frog is updated as follows:

$$D = r \cdot (X_b - X_w), \quad (2)$$

$$X_w(new) = X_w + D, (\|D\| < D_{max}), \quad (3)$$

Where r is a random number between 0 and 1; and D_{max} is the maximum allowed change of frog's position in one jump. Fig.4 demonstrates the original frog leaping rule. If this leaping produces a better solution, it replaces the worst frog. Otherwise, the calculations in (2) and (3) are repeated with regard to the global best frog. If in this case, no improvement becomes possible, the worst frog is deleted and a new

randomly generated frog is replaced. The calculations continue for a predefined number of memetic evolutionary steps within each memplex, and then the whole population is mixed together in the shuffling process. The local evolution and global shuffling is continued until a convergence criterion is satisfied. Usually, the convergence criteria can be defined as follows:

- i. The relative change in the fitness of the best frog within a number of consecutive shuffling iterations is less than a pre-specified tolerance;
- ii. The maximum user-specified number shuffling iterations is reached.

The SFLA will stop when one of the above criteria is achieved first.

Bacterial Foraging Algorithm (BFA)

Natural selection tends to eliminate animals with poor foraging strategies and favor the propagation of genes of those animals that have successful foraging strategies since they are more likely to enjoy reproductive success. After many generations, poor foraging strategies are either eliminated or shaped into good ones. The *E. coli* bacteria that are present in our intestines also undergo a foraging strategy. The control system of these bacteria that dictates how foraging should proceed can be subdivided into four sections namely Chemotaxis, Swarming, Reproduction and Elimination and Dispersal [29].

1) Chemotaxis

This process is achieved through swimming and tumbling via Flagella. Depending upon the rotation of Flagella in each bacterium, it decides whether it should move in a predefined direction (swimming) or altogether in different directions (tumbling), in the entire lifetime. To represent a tumble, a unit length random direction, say ϕ , is generated; this will be used to define the direction of movement after a tumble in a tumble, the position of the i^{th} bacterium is updated as:

$$\theta^i(j+1, k, l) = \theta^i(j, k, l) + C \times \angle \phi \quad (4)$$

Where $\theta^i(j, k, l)$ is the position of the i^{th} bacterium at the j^{th} chemotactic step of the k^{th} reproduction loop in the l^{th} elimination-dispersal event, C is the size of the step taken in the random direction specified by the tumble, $\angle \phi$ is the angle of the direction which is randomly generated in the range of $[0, 2\pi)$.

2) Cell-to-cell Communications

E-coli bacterium has a specific sensing, actuation and decision-making mechanism. As each bacterium moves, it releases attractant to signal other bacteria to swarm towards it. Meanwhile, each bacterium releases repellent to warn other bacteria to keep a safe distance from it. BFA simulates this social behavior by representing the combined cell-to-cell attraction and repelling effect as:

$$J_{cc}(\theta^i(j, k, l), \theta(j, k, l)) = \sum_{t=1}^S J_{cc}^t(\theta^i, \theta) \\ = \sum_{t=1}^S \left[-d_{attract} \exp(-\omega_{attract} \sum_{m=1}^P (\theta_m^i - \theta_m^t)^2) \right] \\ + \sum_{t=1}^S \left[-d_{repellant} \exp(-\omega_{repellant} \sum_{m=1}^P (\theta_m^i - \theta_m^t)^2) \right] \quad (5)$$

Where $J_{cc}(\theta^i, \theta)$ is the cost function value to be added to the actual cost function to be minimized to present a time varying cost function. 'S' is the total number of bacteria and 'P' the number of parameters to be optimized which are present in each bacterium. $d_{attract}$, $\omega_{attract}$, $d_{repellant}$, $\omega_{repellant}$ are different coefficients that are to be chosen properly.

3) Reproduction

In BFA, a fixed total number of reproduction steps, N_{re} is given. Only the first half of populations survive in each reproduce step a surviving bacterium splits into two identical ones, which occupy the same position in the environment as the one in previous step. Thus the population of bacteria keeps constant in each chemotactic step. After N_c chemotactic steps, the fitness values for the i th bacterium in the chemotactic loop are accumulated and calculated by:

$$j_{health}^i = \sum_{j=1}^{N_c+1} j^j(j, k, l) \quad (6)$$

Where j_{health}^i presents the health of the i th bacterium, the smaller the j_{health}^i is, the healthier the bacterium is. To simulate the reproduction character in nature and to accelerate the swarming speed, all the bacteria are sorted according to their health values in an ascending order and each of the first S_r ($S_r = S / 2$), for convenience S is assumed to be a positive even integer) bacteria splits into two bacteria. The characters including location and step length of the mother bacterium are reproduced to the children bacteria. Through this selection process the remaining S_r unhealthier bacteria are eliminated and discarded. To

simplify the algorithm, the number of the bacteria keeps constant in the whole process.

4) Elimination-dispersal

For the purpose of improving the global search ability, elimination-dispersal event is defined after N_{re} steps of reproduction. The bacteria is eliminated and dispersed to random positions in the optimization domain according to the probability P_{ed} . This elimination-dispersal event helps the bacterium avoid being trapped into local optima. The number of the event is denoted as N_{ed} . The flowchart of the BFA has been depicted in Fig. 1.

Problem Formulation

The optimal placement and sizing problems of distributed generation are formulated as a multi-objective function including the network power losses, better voltage regulation and improve the voltage stability. The goal is to converge these three objective functions into one, using the penalty coefficient.

Fitness Function

The objective function is calculated as follows [24]:

$$OF = \text{Min} \left((f_1 + k_1 f_2 + k_2 f_3) + \beta_1 \sum_{i \in N_{DG}} [\max(V_{ni} - V_{ni}^{max}, 0) + \max(V_{ni}^{max} - V_{ni}, 0) + \beta_2 \sum_{i \in N} \max(S_{ni} - S_{ni}^{max}, 0) \right] \quad (7)$$

Where f_1 , f_2 and f_3 are the objective functions to the real power losses, improve voltage profile and for improving voltage stability index, respectively which are expressed in components as follow [30]:

$$f_1 = \sum_{i=2}^{n_n} (P_{gni} - P_{dni} - V_{mi} V_{ni} Y_{ni} \cos(\delta_{mi} - \delta_{ni} + \theta_{ni})) \quad (8)$$

$$f_2 = \sum_{ni=1}^{n_n} (V_{ni} - V_{rated})^2 \quad (9)$$

$$f_3 = \left(\frac{1}{(SI(ni))} \right) \quad ni=2, 3, \dots, n_n \quad (10)$$

Wheres

$$SI(n_2) = |V_{mi}|^4 - 4[P_{ni}(ni)R_{ni} + Q_{ni}(ni)X_{ni}]|V_{mi}|^2 - 4[P_{ni}(ni)R_{ni} + Q_{ni}(ni)X_{ni}]^2 \quad (11)$$

It is very important to identify weak buses for nodes with minimum voltage stability index that are prone to voltage instability. Investigating the voltage stability index behavior demonstrate that the buses which experiencing large voltage drops are weak and

within the context of remedial actions. So, it makes sense to act on controls that will improve the voltage magnitudes at weak buses.

1) Power Flow

The power flow equations to be satisfied for each bus as follow [24]:

$$P_{gni} - P_{dni} - V_{ni} \sum_{j=1}^N V_{nj} Y_{nj} \cos(\delta_{ni} - \delta_{nj} - \theta_{nj}) = 0 \quad (12)$$

$$Q_{gni} - Q_{dni} - V_{ni} \sum_{j=1}^N V_{nj} Y_{nj} \sin(\delta_{ni} - \delta_{nj} - \theta_{nj}) = 0 \quad (13)$$

1) Voltage Profile

The voltage should be kept within standard limits at each bus as follow [24]:

$$V_{ni}^{min} < V_{ni} < V_{ni}^{max} \quad (14)$$

2) DG Units

It is necessary for the DG units to be constrained capacity between the maximum and the minimum levels as follow [24]:

$$P_{gni}^{min} < P_{gni} < P_{gni}^{max} \quad (15)$$

3) Thermal constraint

Thermal limit of distribution lines for the network should not be exceeded [24]:

$$|S_{ni}| \leq |S_{ni}^{max}| \quad (16)$$

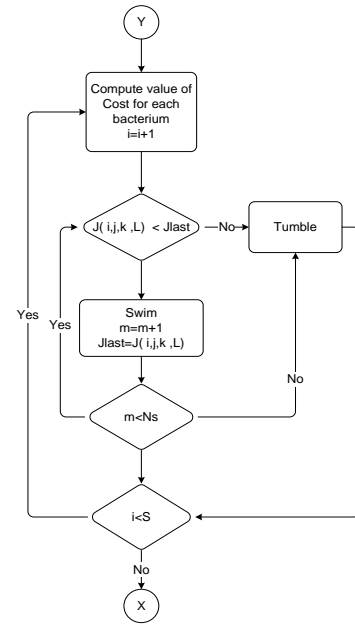
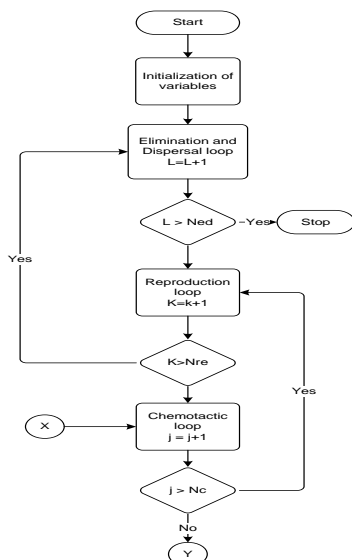


FIGURE 1 FLOWCHART OF BFA

Case Study

The proposed BFA scheme for optimal placement and sizing of DG has been tested on several power systems. Here, the test results for two different distribution systems are presented to demonstrate its effectiveness and the results are investigated. The values of the objective functions before the installation of DGs have been shown in Table 2.

TABLE 2 OBJECTIVE FUNCTION VALUE OF THE SYSTEMS BEFORE DG INSTALLATION

System	Objective function value		
	F1	F2	F3
33-Bus	0.2109	0.3141	1.4907
69-Bus	0.2217	0.2197	1.4509

1) Coding and Decoding of the Solution

The coded variables are, therefore, the candidate locals for DG installation and the respective when applying genetic algorithms to optimize the DG allocation and sizing problem, an important aspect is the coding of the potential solutions. In a general way, a potential solution is a configuration of the network with the DG units size of the units. In that sense, each chromosome is coded through a vector whose dimension is the number of candidate points and whose content is the size of the installed units. The chromosome coding used in the proposed methodology is of the integer type {0, 1, 2, 3,}. In the DG allocation process, number 0

The adjustable value of BFA, GA, SFLA algorithms for simulation are given in table 1.

TABLE 1 ADJUSTED PARAMETERS OF BFA, GA, SFLA ALGORITHMS

BFA parameters		GA parameters	
number of bacteria	6	population size	50
dimension of optimization process	6	number of optimization variables	6
number of swimming step	8	Noise band	$0.5*[3\ 3\ 3\ 1\ 1\ 1]$
number of chemotaxis step	30	mutation rate	0.8
number of reproduction	5	cross over rate	0.2
number of elimination and dispersal	5	Creation of initial population	rand(50,6)
probability index of elimination and dispersal	0.35		
normalized distribution	Rand (6 , 6)		
step size for each bacterium	0.05		
elimination-dispersal loop index	0		
reproduction loop index	0		
chemotaxis loop index	0		

means no DG unit, while the other numbers represent sequentially a DG unit from a list of candidates provided for each candidate installation place. The decoding of the GA solution is based on the same idea, translating a number in the chromosome into the respective DG unit.

2) 33 Bus Radial Distribution Systems

At first the proposed technique is applied on a radial system using the total load 3.72 MW, 2.3 MVar, 33 bus and 32 branches as it is shown in Fig2. The real power and reactive power losses in the system are 210.998 (kW) and 143 (kVar) respectively. The voltage profile before installation DG and after optimally placing DGs, and voltage stability index are given in Fig. 3 and 4, respectively. The minimum fitness value evaluating process has been shown in Fig. 5. Table 3 demonstrates the results for optimal placement and sizing problems of distributed generation.

3) 69 Bus Radial Distribution Systems

The other system employed to evaluate the proposed method is the 69 bus radial distribution system that has the total load of 3.80 MW and 2.69 MVar and it is demonstrated in Fig. 6. For more details, the voltage profile and voltage stability index are illustrated in Fig.9 and Fig. 8. The minimum fitness value evaluating process DG location and capacities are represented in Fig 11 and Table 4.

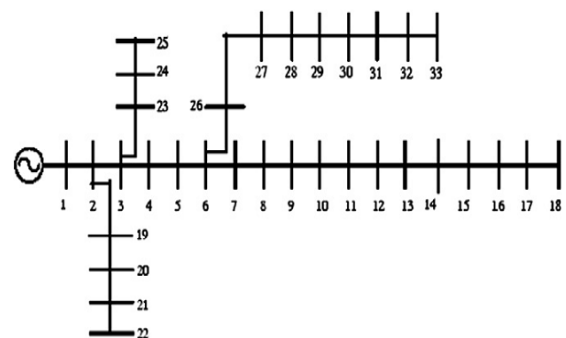


FIGURE 2 THE 33 BUS RADIAL DISTRIBUTION SYSTEM

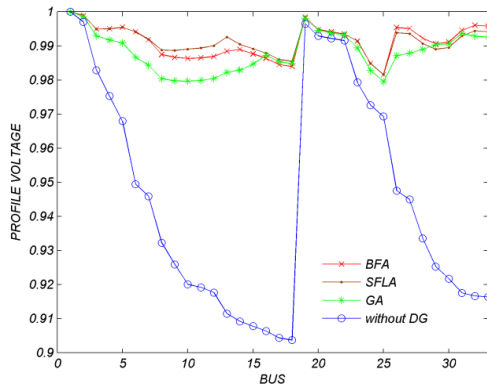


FIGURE 3 VOLTAGE PROFILE OF 33-BUS

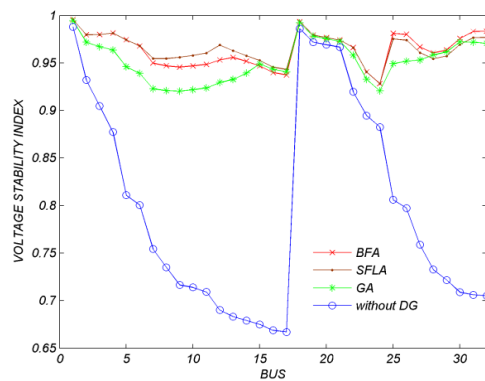


FIGURE 4 VOLTAGE STABILITY INDEX OF 33-BUS

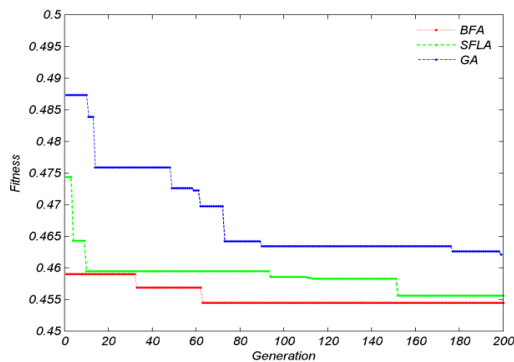


FIGURE 5 VARIATIONS OF OBJECTIVE FUNCTION

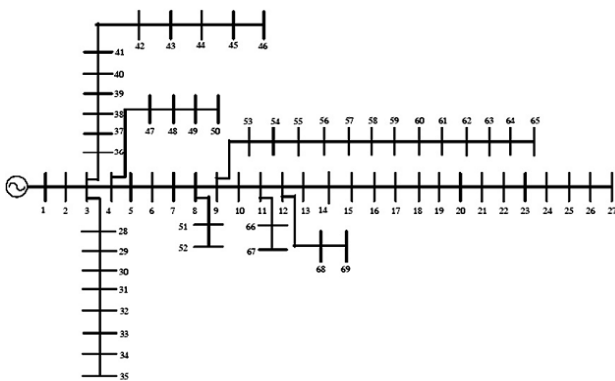


FIGURE 6 THE 69 BUS RADIAL DISTRIBUTION SYSTEM

The results presented in table 2 and table 3, shows that the BFA is effective for optimal placement and sizing of DG. In addition, the running time for the BFA was faster in comparison with the others. As it obvious from the Fig. 5 and fig. 7, the voltage profiles at all nodes for radial transmission systems have improved. Fig. 5 and fig.8 depict Convergence profile of each bus in 33 and 69 bus distribution systems. It can be seen that the convergence of BFA algorithm is faster than SFLA and GA algorithm and this is because BFA algorithm provides the correct answers with high accuracy in the initial iterations which makes the responding time of this algorithm extremely fast. The voltage stability for two systems has been shown in Fig 4 and 8. As it obvious from the figures, the voltage stability after installing DGs has been improved.

4) Stability and Voltage Regulation

Voltage stability index in bus 18 from the first system and bus 61 from the second were low before DG installation. This could cause instability in the networks in the presence of disturbances. After DG installation, the three methods showed major improvements, Figs. 4 and 8. Besides, the Figs. 3 and 7 are demonstrating that the voltage regulation index is at highest for BFA and for the GA is the lowest.

Conclusion

In this paper, the BFA is presented for optimal placement and sizing of DG units. The proposed BFA algorithm for optimal placement of DG is easy in performance without additional computational complexity. The capability of the proposed approach is tested on 33 and 69 bus systems to minimize the losses, increase the voltage stability and improve the voltage profile. The simulation results show that the BFA yields has better convergence characteristics and performance compared with the other heuristic methods such as GA and SFLA. Also the proposed technique exhibits a higher capability in finding optimum solutions by taking into account the active power and reactive power losses for objective function.

TABLE 3 PERFORMANCE ANALYSIS OF THE 33-BUS SYSTEM AFTER DG INSTALLATION

Method	Objective function value			Bus.no	DG size(MW)
	F1	F2	F3		
BFA	0.0921	0.0022	1.0247	25	1.1770
				13	0.7771
				31	1.1993
SFLA	0.0940	0.0028	1.0236	31	1.1944
				12	0.8894
				5	1.0664
GA	0.1005	0.0058	1.0302	28	0.6632
				15	0.8177
				30	1.1297

TABLE 4 PERFORMANCE ANALYSIS OF THE 69-BUS SYSTEM AFTER DG INSTALLATION

Method	Objective function value			Bus.no	DG size(MW)
	F1	F2	F3		
BFA	0.0921	0.0022	1.0247	25	1.1770
				13	0.7771
				31	1.1993
SFLA	0.0940	0.0028	1.0236	31	1.1944
				12	0.8894
				5	1.0664
GA	0.1005	0.0058	1.0302	28	0.6632
				15	0.8177
				30	1.1297

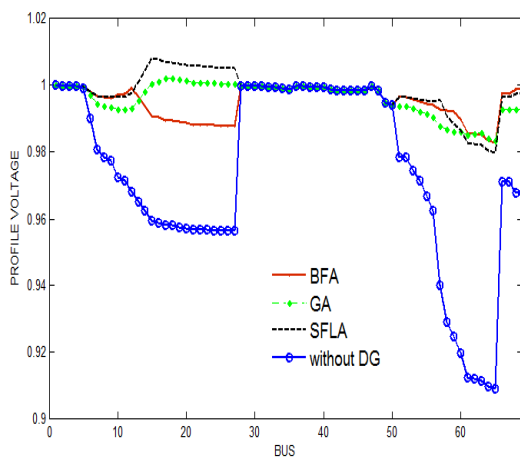


FIGURE 7 VOLTAGE PROFILE OF 69-BUS

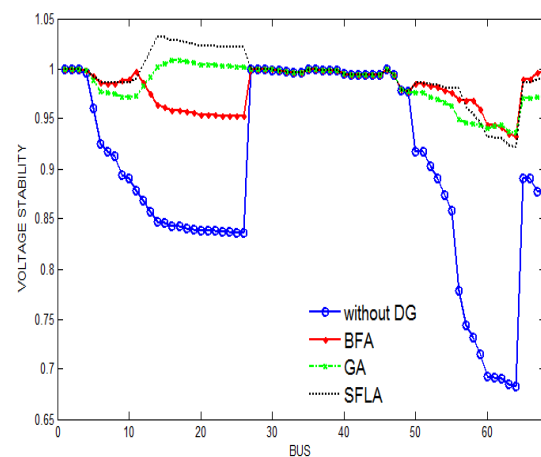


FIGURE 8 VOLTAGE STABILITY INDEX OF 69-BUS

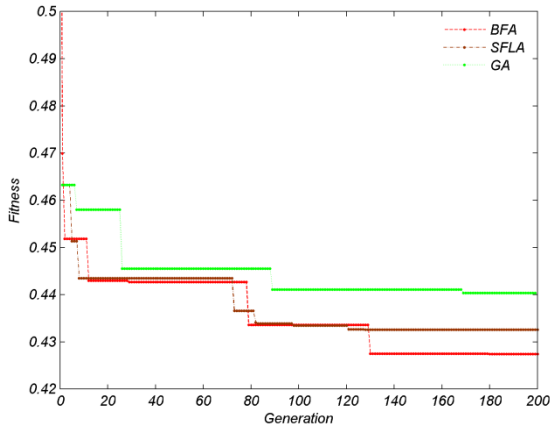


FIGURE 9 VARIATIONS OF OBJECTIVE FUNCTION

Appendix

n_n	total number of buses in the given RDS
n_i	receiving bus number ($n_i = 2, 3, \dots, n$)
m_i	bus number that sending power to bus n_i ($m_1 = n_1 = 1$)
i	branch number that fed bus n_i
N_{DG}	total number of DG
P_{gni}	active power output of the generator at bus n_i
Q_{gni}	reactive power output of the generator at bus n_i
P_{dni}	active power demand at bus n_i
Q_{dni}	reactive power demand at bus n_i
$P_{ni}(n_i)$	total real power load fed through bus n_i
$Q_{ni}(n_i)$	total reactive power load through bus n_i
P_{gni}^{\min}	Minimum active power of DG at bus n_i
P_{gni}^{\max}	Maximum active power of DG at bus n_i
V_{ni}	voltage of bus n_i
V_{mi}	voltage of bus m_i
V_{ni}^{\min}	Minimum voltage at bus n_i
V_{ni}^{\max}	Maximum voltage at bus n_i
$ S_{ni}^{\max} $	Maximum apparent power at bus n_i
Y_{ni}	admittance between bus n_i and bus m_i
θ_{ni}	Phase angle of $Y_i = Y_{ni} \angle \theta_{ni}$
δ_{ni}	Phase angle of voltage at bus n_i $V_{ni} = V_{ni} \angle \delta_{ni}$

δ_{mi}	Phase angle of voltage at bus m_i
V_{rated}	rated voltage (1 p.u.)
$SI_{(n_i)}$	voltage stability index of node n_i . ($n_i = 2, 3, \dots, n$)
β_1	penalty coefficient, 0.32
β_2	penalty coefficient, 0.3
r_1	penalty coefficient ($k_1 = 0.6$)
r_2	penalty coefficient ($k_2 = 0.35$)
f_1	network real power losses (pu)
f_2	network voltage profile (pu)
f_3	network voltage stability index (pu)

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